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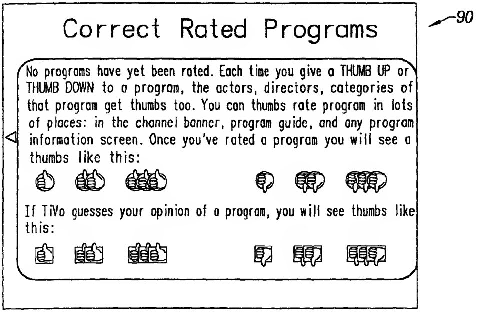
(54) Title: INTELLIGENT SYSTEM AND METHODS OF RECOMMENDING MEDIA CONTENT ITEMS BASED ON USER PREFERENCES



(57) Abstract: A system and method for making program recommendations to users of a network-based video recording system utilizes expressed preferences as inputs to collaborative filtering and Bayesian predictive algorithms to rate television programs using a graphical rating system. The predictive algorithms are adaptive, improving in accuracy as more programs are rated.

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INTELLIGENT SYSTEM AND METHODS OF RECOMMENDING MEDIA CONTENT ITEMS BASED ON USER PREFERENCES

BACKGROUND OF THE INVENTION

FIELD OF THE INVENTION

The present invention relates to automated systems and methods for recommending items to users. More particularly, the invention relates to an adaptive network-based system and methods for predicting ratings for items of media content according to how likely they are to appeal to a user. The invention integrates multiple prediction algorithms and provides heuristics for selecting the most suitable algorithm for making a prediction for any single item, creating a suggestion and rating system having exceptional robustness and predictive accuracy.

DESCRIPTION OF THE PRIOR ART

The prior art provides various systems for filtering, suggesting and rating. Filtering, suggesting and rating, while they may employ similar methods, constitute separate challenges. In the presence of a large amount of content, be it merchandise, or videos, or newsgroup articles, filtration systems aim to limit the amount of content a user deals with, by presenting only that content that correlates most closely with the users preferences. As such, their essential function is one of exclusion. Suggestion systems aim to direct a user's attention to items they may not have been aware of that are likely to appeal to them, based on their preferences. Thus, their essential function is one of inclusion. Rating systems assign ratings to content items, according to a user's expressed preferences. Hence, their essential function is one of ordering. Occasionally, systems are provided that are capable of performing

more than one of the essential functions of excluding, including and ordering.

Some of the prior art examples are adaptive in nature; that is, they are capable of accommodating themselves to changing conditions, in a process that is analogous to learning. For example, over time, a user's preferences may change, sometimes gradually, and sometimes abruptly. Adaptive systems have the capacity to adapt to a user's changing preferences without any explicit input from the user. Often, adaptive systems must be taught, that is, their engines must be initialized with starting values. The teaching process usually consists of the user explicitly indicating their preferences. After being taught, adaptive systems make inferences by monitoring various implicit indicators or the user's preferences.

H. Strubbe, *System and method for automatically correlating user preferences with a T.V. program information database*, U.S. Patent No. 5,223,924 (Jun 29, 1993) and H. Strubbe, *System and method for finding a movie of interest in a large movie database*, U.S. Patent No. 5,483,278 (January 9, 1996) provide systems for rating movies and television programs by a user and correlating program information for unrated programs with the user's ratings, so that a program database customized to the user may be created. To rate the programs, the user accesses program information either by time slot or channel, and assigns a Boolean rating of "like" or "dislike." A free-text search algorithm searches a text summary in the program information records rated by the user. The significant words of the text summary are tallied and weighted. A free-text search of unrated records is performed, and a retrieval values is computed. Records with retrieval values are judged to be programs likely to appeal to the user and are added to the database of preferred programs. While the described systems effectively allow the user to filter television programming and movies, it would be desirable to provide a scalar rating system, in which the user is able to express degrees of preference rather than a simple 'yes' or 'no.' Since free-text searches are computationally expensive, it would be advantageous to

provide a more efficient, content-based algorithm. It would also be desirable to provide different types or predictive algorithms, thereby increasing prediction accuracy. In addition to assigning overall ratings to programs, it would be a great advantage to provide the user with the capability of rating individual program features, such as the actors or the director.

F. Herz, J. Eisner, L. Ungar, M. Marcus, *System for generation of user profiles for a system for customized electronic identification of desirable objects*, U.S. Patent No. 5,754,939 (May 19, 1998) describes a client server-based system for retrieving items of interest to a user. An interest summary of the user is prepared, by querying the user about their interests. Each target item available over the network is described by a target profile. Target profiles are compared to each other and clustered according to similarity. Clusters and individual target items are compared with the user interest summary. Items likely to be of interest to the user are presented in a ranked listing. The user profile is stored on a proxy server, and security measures are provided to safeguard the user's identity. Relevance feedback is provided by monitoring which items a user expresses interest in. While efforts are made to preserve the user's confidentiality through various security measures, it would be desirable to provide a system in which the user's profile is stored locally, on the client side, and communication between the server and the client is stateless, so that the server is completely ignorant of the user's identity. It would also be desirable to provide a prediction engine on the client side, again rendering a stateful connection between client and server unnecessary. In addition to implicit relevance feedback, it would be an advantage to allow the user to correct their profile, thus allowing even greater predictive accuracy.

G. Graves, B. O'Conner, A. Barker, *Apparatus and method of selecting video programs based on viewer's preferences*, U.S. Patent No. 5,410, 344 (April 25, 1995) describe a method for selecting television programs according to expressed viewer preferences that employs an adaptive prediction algorithm. Television programs are described in terms of attributes. A viewer

explicitly rates different attribute-value pairs, also known as features. Based on these explicit viewer ratings, a neural network rates television programs. Programs with a high enough score are automatically recorded for viewing at a later time. The described method, however, must use explicit ratings, it does not employ or generate implicit ratings. Furthermore, the described method provides only a single prediction algorithm, limiting its versatility and robustness.

J. Hey, *System and method for recommending items*, U.S. Patent No. 4,996,642 (February 26, 1991). Employs a conventional collaborative filtering algorithm to recommend movies to a customer from the inventory in a video store. The customer uses a scalar rating system to rate movies they have viewed. The resulting profile is paired with profiles of other customers who have rated at least a portion of those selections rated by the first customer, and an agreement scalar is computed for each of the pairings. Based on these pairings, a group of recommending customers is defined for the first customer. D. Payton, *Virtual on-demand digital information delivery system and method*, U.S. Patent No. 5,790,935 (August 4, 1998) describes a digital information system that delivers virtual on-demand information over digital transport systems. A collaborative filtering algorithm predicts content items that might be of interest to each subscriber. A. Chislenko, Y. Lashkari, D. Tiu, M. Metral, J. McNulty, *Method and apparatus for efficiently recommending items using automated collaborative filtering and feature-guided automated collaborative filtering*, U. S. Patent No. 6,092,049 (July 18, 2000) describe a method for recommending items to users using automated collaborative filtering. As with the other references described, a conventional collaborative filtering implementation, in which users are correlated to other users, is provided. B. Miller, J. Konstan, J. Riedl, *System, method and article of manufacture for utilizing implicit ratings in collaborative filters*, U. S. Patent No. 6,108,493 (August 22, 2000) describe a prediction information system utilizing collaborative filters. Unlike most collaborative filtering implementations, which operate on explicit ratings, the described system utilizes implicit measures. The accuracy of prediction attainable with

collaborative filtering has been shown to be quite high. Nevertheless, conventional collaborative filtering implementations all require maintaining user information in a central place, such as on a server, leading to concerns about the user's privacy. Subsequently, similarities between pairs of users are computed on the server. It would be desirable to provide a collaborative filtering implementation based on similarity between pairs of items, rendering it unnecessary to maintain user information on a server, and eliminating the necessity of exchanging state information between client and server.

D. Whiteis, *System and method for recommending items to a user*, U.S. Patent No. 5,749,081 (May 5, 1998) describes a system for recommending items of merchandise to a customer at the point of sale based on items already selected. Unlike the collaborative filtering implementations described above, the Whiteis system correlates items, rather than users, by tracking the number of times a pair of items occurs together in the same purchase. Based on the number of times a pair occurs, an adjusted weight is calculated that is taken to be an index of similarity between the two items of the pair. The described system is simple and easily implemented and is well suited for point-of-sale use. However, since similarity is calculated simply on whether a pair occurred in the same purchase, it can only be a very general approximation of similarity. For example, in a video store, a father may be select "Lion King" for his children and "Body Heat" for he and his wife. In the present system, that purchase would be listed as a correlating pair, albeit a weakly correlating pair if it did not occur frequently in the total population of pairs. Furthermore, it would be an advantage to filter the weights to eliminate pairs that correlate weakly. It would also be an advantage to provide information about pairs that anti-correlate.

A. Lang, D Kosak, *Information system and method for filtering a massive flow of information entities to meet user information classification needs*, U.S. Patent No. 5,867,799 (February 2, 1999) provide an apparatus, method and computer program product for information filtering in a computer system

receiving a data stream from a computer network. Several layers of adaptive filtering are provided, both content-based and collaborative, to ensure that a receiver receives only those content items that correlate very highly with their preferences. There are individual user filters and community filters. The essential function of the system according to Lang, *et al.* is overwhelmingly one of exclusion, with the multiplicity of filter layers. However in a system, the aim of which is to predict items most likely to appeal to a user, and suggest items likely to appeal to a user, the redundant filtering of the present system would limit the amount of content available to the user, thus limiting user choices rather than providing new and unexpected alternatives.

Thus, there exists a need in the art for a system for predicting a rating for an item according to how much it will appeal to a user. It would be advantageous to provide multiple prediction engines that are capable of providing the most accurate prediction for any particular item. It would be highly desirable to provide a convenient user interface for teaching the system the user's preferences. Furthermore, it would be an advantage for the system to have an adaptive capability, so that it can learn and adapt to shifts in user preferences. It would be desirable to provide a distributed collaborative filtering engine that guaranteed a user's privacy by eliminating the necessity of correlating the user to other user's or groups of users. It would be a great advantage to calculate similarity between items, rather than between users and to perform such calculation on the client side, eliminating the necessity of a stateful connection between the server and the client. It would be a significant technological advance to provide an adaptive modeling prediction engine that accepted both explicit user ratings and had the capability of inferring user ratings in the absence of explicit ratings. It would be a great convenience to display the output of the various prediction engines in a single, integrated list.

SUMMARY OF THE INVENTION

The invention provides a network-based intelligent system and method for predicting rating for items of media content according to how likely they are to appeal to a user based on the user's own earlier ratings. Collaborative filtering and content-based prediction algorithms are integrated into a single, network-based system. System heuristics determine which of the provided algorithms provide the most reliable predictor for any single new content item.

In a preferred embodiment of the invention, a network-based video recording system rates television programs according to the likelihood that they will appeal to a user, based on the user's own previous ratings of television programming. Individual recording units, clients, are in intermittent communication with a server. A user interface is provided in which the user teaches the system by recording their programming preferences. Using an interactive rating system that employs a "thumbs up" and "thumbs down" metaphor for favorable and unfavorable ratings, respectively, individual users may give an overall rating to a program, or they may rate individual features of the program: for example, directors, actors, and genres; provided in interactive lists. The users preferences are then used as inputs to one or more predictive algorithms.

A collaborative filtering algorithm is provided, in which individual items are correlated to each other, instead of the usual approach of correlating users to each other. Lists of rated items are periodically uploaded from individual clients to the server. The ratings are extracted from the lists and stored in matrices on the server, eliminating the necessity of keeping client state information on the server, thus advantageously providing an important privacy safeguard. The server computes correlation factors for pairs of programs and provides them to the client in a correlating items table. The client searches the table for pairs containing programs already rated by the

user. Thus, other programs not rated by the user, which correlate to the rated program, can be assigned a similar rating.

In the absence of up-to-date correlating items data, an adaptive modeling algorithm is also provided that works by using content-based filtering: in particular it uses the features of a program and a user's prior preferences on those features to arrive at a prediction of how much the user would like a program. In the absence of explicit ratings of a program's features, a modified naïve Bayes algorithm infers ratings of the program features based on previous ratings by the user of programs containing at least one of the features. Based on the inferred feature ratings, a prediction is made of how much the user would like the program. Unlike conventional implementations of the naïve Bayes algorithm, the invention extends the Bayes algorithm to handle multi-valued features, *i.e.* a program generally has more than one actor, or it may be classified in more than one genre. Additionally, the invention provides for the integration of explicit advice, the expressed user preferences, with inferred ratings.

The user is also provided with the capability of correcting preferences, either explicit ones or inferred ones. Thus, the user may optimize the preference profile in order to obtain predictions that coincide with their expectations more closely.

BRIEF DESCRIPTION OF THE DRAWINGS

Figure 1 provides a block diagram of the functional architecture of a network based system for predicting the likelihood that a an item of media content will appeal to a user based on previous ratings of content items by the user, according to the invention;

Figure 2 shows a screen from a user interface to the system of Figure 1, wherein suggested items are displayed to a user, and access is gained to a

user interface, wherein a user teaches the system the user's preferences, according to the invention;

Figure 3 shows a top-level screen of the teaching interface of Figure 2, according to the invention;

Figures 4 and 5 show screens from the teaching interface of Figure 2 for teaching content category and sub-category preferences, according to the invention;

Figure 6 shows a screen from the teaching interface of Figure 2 for teaching actor preferences, according to the invention;

Figure 7 shows a screen from the teaching interface of Figure 2 for correcting user ratings and predicted ratings of actors, according to the invention;

Figure 8 shows a screen from the teaching interface of Figure 2 for teaching program preferences, according to the invention;

Figure 9 shows a screen from the teaching interface of Figure 2 for correcting user ratings and predicted ratings of programs, according to the invention; and

Figure 10 shows the block diagram of a distributed system collaborative filtering prediction system, within the system of Figure 1, according to the invention.

DETAILED DESCRIPTION OF THE INVENTION

Referring now to Figure 1, shown is a block diagram of an intelligent, distributed system for recommending items of media content to a user, based on the user's expressed preferences. Although Figure 1 illustrates a single

client, such illustration is understood to be exemplary only. One skilled in the art will readily appreciate that the system includes a plurality of clients. A client 10, over a conventional network connection 12, is in intermittent communication with a server. A user interface 14 is provided, wherein the user teaches the system the user's preferences concerning programs, categories of programs and program features. When the system has built a sufficient knowledge base, a series of prediction engines having an adaptive capability, predicts ratings for unrated program items, based on the user's expressed preferences. The preferred method employs a novel, client-side collaborative filtering engine 17. Lists of items rated by the user 15 are transmitted to the server 11, where they are aggregated, with the rated items information from many other users, into a single list. A listing of correlating items is generated 19 and transmitted back to the client 10, where the collaborative filtering engine predicts ratings based on the correlation provided by the server, and the user's previous ratings.

It may happen that up-to-date correlation information is unavailable. In such event, an adaptive, content-based prediction engine 18 predicts ratings of unrated program items. Preferably, the content-based engine employs explicit user ratings of various program features as inputs. However, in the absence of explicit ratings, a naïve Bayes classifier infers ratings from which a rating is predicted.

The invention is created and implemented using conventional programming methods well-known to those skilled in the arts of computer programming and software engineering.

METHOD OF TEACHING BY USERS

The invented system allows users to rate an item, from -3 to 3 (7 levels), wherein negative ratings are unfavorable and positive ratings are favorable. Ratings are expressed using a graphical metaphor, in which "thumbs up"

indicate favorable ratings and "thumbs down" indicate unfavorable ratings. 0, indicated by an absence of thumbs, is a neutral rating. Typically, the user assigns thumbs to a program or a program feature by depressing a button on a remote control that is provided with the client unit. Referring to Figure 2, a suggestion screen 20 of the invented system displays a listing of suggested programs 21 accompanied by their rating icons 22. Close to the top of the screen, beneath the banner, a selection bar is positioned over a menu item 23 that grants access to the teaching screens. The suggestions 21 are displayed in a descending sort according to the number of thumbs 22. An arrow-shaped cursor 24 allows the user to scroll through the entire list of suggestions. Referring now to Figure 3, the first screen 30 of a user interface for assigning ratings to television programs and individual program features is shown. Selections for rating program category 31 or genre, individual programs 32, actors 33 and directors 34 are provided. The user manipulates the various interface elements by means of the provided remote control. As Figures 4 and 5 show, selecting the 'teach category' option 31, navigates the user to a 'teach category' screen 40 and subsequently to a 'teach sub-categories' screen 50. Selecting any one of the displayed categories or sub-categories allows the user to assign 'thumbs' ratings to the selected categories, although the display is not immediately redrawn to reflect the user's ratings. Upon selecting the 'teach actors' option 33, the user is presented with several further options, two of which are shown in Figures 6 and 7. As previously indicated, the user's preferences, expressed as ratings, are necessary as input to the various predictive algorithms of the invention. Before the algorithms are able to start providing the user with predictive ratings, they must be "taught" or initialized with a minimum amount of user preference data. In the course of viewing or selecting a program for recording, viewers may assign a rating to a program. By assigning ratings in this way, however it can take a fairly long time before the preference database has accumulated enough data to teach the predictive algorithms. In order to accelerate the process of accumulating preference data, the various teaching screens with their lists are provided, so that the user may initially go through the lists and systematically rate a threshold number of

programs and individual features. To facilitate the process of working through the feature list, lists of varying lengths are provided. For example a 'Teach famous actors' screen 60 provides a compact list 61 of high-profile actors. Thus, the process of rating actors, by the user is greatly facilitated. Additionally, a 'Teach all actors' screen (not shown) provides a comprehensive list of actors from which the user may also work. Figure 6 also shows the manner of assigning ratings. The user is provided with a menu of possible ratings 62 from which they select a rating for the corresponding actor. After selecting the rating, the selected rating is highlighted. As previously described, the user interface is not immediately repainted to reflect the user's rating selection.

In Figure 7, a 'Correct rated actors' screen 70 is shown. While the example shown indicates that no actors have yet been rated, if actors had been rated, the user would be presented with a list of rated actors, similar to lists already shown. As will be described in greater detail further below, provision is made for distinguishing between user-assigned ratings and predicted ratings assigned by the system. Separate, similar, but distinct icons are provided for user ratings 71 and predicted ratings 72. In the event that actors had been rated, the user would be provided with a single, aggregate list of all rated actors, both user-rated, and those for whom the system has predicted ratings. Thus, the user may correct their own ratings, and they may revise predicted ratings. Advantageously, the ability to view and correct predicted ratings allows the user to browse the basis features that were used by the system to make a particular prediction for a show. This will allow the user to directly modify his or her preference profile in order to obtain predictions more in line with what he or she expected. As Figures 8 and 9 show, the process of rating programs and correcting rated programs is almost identical to that for actors.

While screens are not shown for all attributes, the process of rating attributes and correcting them is virtually identical across the entire selection of attributes. The preferred embodiment of the invention provides 'actors,'

'genre' and 'directors' as program attributes. However, the list of attributes need not be so limited. The manner of providing the user interface employs conventional techniques of computer programming and graphics display commonly known to those skilled in the arts of computer programming, software engineering, and user interface design.

As described above, as a preference profile is built, the user may explicitly rate programs and individual programs, and he or she may correct ratings, either their own, or predicted ratings. Additionally, other system heuristics may apply a rating to an item. For example, when a user selects a program to be recorded, the system automatically assigns one thumb up, corresponding to a rating of one, to that item if the user had not already rated the program. Other heuristics are based on whether a program was watched after it was recorded, and for how long.

PREDICTING PROGRAM RATINGS

As previously described, the user teaches the system his or her preferences by assigning overall ratings to programs they are familiar with, and rating individual program elements, such as actors and genres. Subsequently, the preferences are fed to one or more predictive algorithms to assign ratings to programs that predict the likelihood of the user liking them. The preferred embodiment of the invention includes a collaborative filtering algorithm and a content-based adaptive modeling algorithm.

The total number of programs available to the user may be considered to be a pool, or a population of items. As previously described, the user assigns ratings to a subset of that pool using discrete ratings. In the preferred embodiment of the invention, the rating is measured as a number of thumbs from -3 to 3, with 0 connoting a neutral rating. There also exists a pool or population of program elements, or features, a portion of which have been rated by the user according to the same rating system.

COLLABORATIVE FILTERING

The purpose of collaborative filtering is to use preferences expressed by other users/viewers in order to make better predictions for the kinds of programs a viewer may like. In order to rate how much the current user will like a program to be rated, "Friends," for example, the collaborative algorithm evaluates the other programs that the user has rated, for example, two thumbs up for "Frasier," and uses the correlating items table downloaded from the server to make a prediction for "Friends." The correlating items table may indicate that "Friends" and "Frasier" are sixty-six per cent correlated and "Friends" and "Seinfeld" are thirty-three per cent correlated. Assuming that the user has expressed 2 thumbs up for "Frasier" and 1 thumb up for "Seinfeld," the algorithm will predict 1.6 thumbs up for "Friends, " closer to 2 thumbs up than 1 thumb up. This prediction will be rounded to 2 thumbs up in the user interface, and thus the prediction is that the user will like "Friends" to the extent of 2 thumbs up.

The invented implementation of collaborative filtering provides the following advantages:

1. **No person-to-person correlation.**

   The server 11, which collects "anonymized" preferences profiles from the individual clients, does not as is conventionally done, compute a correlation between pairs of users. Instead, it computes a correlation between pairs of programs. Thus, no sensitive or personal user information is ever kept or needed on the server. Preferences information is http posted from the client to the server; once the network connection is terminated, the server has an anonymous set of preferences – it doesn't matter whose preferences they are. In order to guarantee the user anonymity. the entire preference database of each client is periodically uploaded to the server. Thus there is no need to issue cookies or maintain any client state information on the server.

2. **Distributed, or local computation of program ratings.**

Pairs of programs are evaluated that:

- are sufficiently highly correlated to be good predictors of each other, and
- that have been rated by enough viewers.

The server then transmits to each client the correlations for each significant program pair in a correlating items table. Next, the client filters these pairs to find only those pairs for which one of the programs in the pair has been rated by the user. Thus, continuing with the example above, the server may have calculated a high correlation between "Spin City" and "Friends," based on the preferences information from thousands of other users. However, since the user at hand has rated neither "Spin City" nor "Friends," that correlation is not useful, therefore the client will filter that pair. On the other hand, since the user has rated "Frasier" and "Seinfeld," the pairs

[Frasier -> Friends 0.66] and [Seinfeld -> Friends 0.33] are retained and used as inputs to the collaborative filtering algorithm.

3. The architecture of the collaborative filtering server is highly parallellizable and consists of stages that pre-filter shows and pairs of shows so that computing correlation, a computationally expensive process, for all pairs may be avoided.

4. **Carouselling of correlations from server to clients.**

The tables of correlating items are broadcast daily, but since correlations between pairs do not change drastically from day to day, each client only processes correlations periodically, eliminating the necessity of recomputing correlations on a daily basis.

5. **Robustness of collaborative filtering engine.**

Each stage of the collaborative filtering engine may be implemented by several computers. Thus, if one computer is non-functional for a short period of time, correlation computations allocated to that

computer will queue up at its feeder computer, and the process is delayed somewhat without a noticeable disruption of service to the user. Additionally, since correlations do not change greatly from month to month, losing a portion of the correlations only results in a graceful degradation of prediction quality, and not a catastrophic loss in quality.

Figure 10 provides a diagram of the functional architecture of a distributed collaborative filtering engine, according to the invention. A client 10 is in intermittent contact with a server 11 over a network connection 12. As indicated above, the server-side architecture may be implemented across several computers, or it may be implemented on a single computer having multiple functional units. In the preferred embodiment of the invention, the network connection is either a dial-up connection over publicly available telecommunications networks or a satellite connection. However, other types of network connections known to those skilled in the art are within the spirit and scope of the invention. According to the preferred embodiment of the invention, the client 10 and the server 11 are in communication for a brief period on a daily basis so that the client may transmit rated items 15 to the server 11 and receive the correlating items table 104b broadcast from the server 11 periodically. A listing of unrated items 16, wherein the unrated items consist of television programs, is resident on the client 10. The list of unrated programs is presented to the user on a conventional display means 25. The display means may be a television screen, A CRT monitor, an LCD display, or any other generally known display means. During the period of daily contact with the server, the list of unrated items 16 is updated. An interactive user interface 14, allows the user to rate items known to the user using the graphical rating system previously described. As items are rated by the user, the rated items are saved to a listing of rated items 15. In the preferred embodiment of the invention, the listing of rated items 15 exists as a conventional table. However, other commonly known data structures, such as delimited text files, would be equally suitable.

When the client 10 and the server 11 are in communication, the list of rated items 15 is transmitted to the server. The correlating items table 104a is generated using the rated items 16 input of all users, or a random sample of them. A frequency filter 101 blocks items and pairs of items that have not been rated by a sufficient number of users, thus minimizing the storage required for the pair matrices 102. The filter thresholds also serve to assure a minimum quality of the correlation calculations, since they get more accurate with more input due to their adaptive nature. Filtering takes place in two stages. The first stage tracks the frequency of any unique item. If the frequency is too low, the item and user rating are not considered. The second stage monitors frequencies of unique pairs. If a pair's frequency is too low, the pair is not longer considered.

Pair matrices store the user ratings in an n by n matrix, where n is the number of distinct levels on the rating scale used by users. As previously described, in the current embodiment of the invention, there are seven discretet ratings: -3,

-2, -1, 0, 1, 2 and 3. Thus, each pair matrix is a 7x7 matrix. The foregoing desdription is not intended to be limiting. Other rating scales, resulting in matrices of other dimensions are also suitable. Provided below is an algorithm for storing ratings to the pair matrices 102:

1. Get a pair of ratings for a pair of items.
2. Find the matrix for that pair, and create if it does not exist yet.
3) Using the rating pair as index into the matrix, locate the cell for that rating pair.
4) Increment the cell's value by one.
5) Go to 1.

Using commonly known analytical methods, a correlation factor is calculated from the pair matrix for each program pair. Every matrix yields a correlation factor from approximately -1 to 1.

The correlation filter 103 prevents pairs of items from being considered that have correlation factors close to 0. Thus, pairs that only correlate weakly are not used. Those pairs that pass the correlation filter 103 are assembled into a correlating items table 104a, which lists all other significantly correlating items for every item. That list, or a part thereof, is distributed back to the client 10.

On the client side, a predictive engine assigns a rating to a new unrated item that is predictive of how much that item will appeal to the user, based on the rated items 16 and the correlating items table, that describes the correlations between items. Provided below is an algorithm for rating an unrated item.

1. Get an unrated item (program).

2. Search for the item in the correlating items table. If not found, no prediction is made - Go to 1.

3. Create a work list of correlation factors for all correlating items the user has rated, together with the user ratings.

4. If the work list is empty, no prediction is made. Go to 1.

5. Make sure the work list contains a fixed number of items.
   - If the work list exceeds the fixed number, remove those that relate to the worst correlating item (program).
   - If the list is too short, pad it with correlation factors of 1 and a neutral rating.

   The fixed length selected is a matter of design choice; the intent is to provide a fixed-length list of input so that results can be compared fairly when predicting for different unrated items, when the amount of data available for prediction varies.

6. The sum of (rating * correlation) of all items in the work list, divided by

the sum of the absolute values of correlation factors for all items constitutes a prediction a rating for the item that is predictive of the degree to which the item will appeal to the user.

ENHANCEMENTS TO ENSURE PRIVACY

As described above, the system is designed to safeguard the user's anonymity. There are many clients, and over time more and more programs are rated. When a particular client has rated a few more programs, the server would need to include that input in the Pair Matrices to further increase the accuracy and scope of the correlations. Conventionally, only the new data would be transmitted to the server to permit it to do the work of updating the pair matrices. However, to do that, the server would need to save the state for each client and identify the client in order to know all the items rated by that client. Privacy requirements disallow any method of identifying the client when accepting input. Therefore, the rated items list is sent in its entirety, on a periodic basis. Clients use the same time window for sending in their lists, at randomly chosen times. The server accepts input as described earlier, keeping counts in the matrices. In addition, the server compensates for the repetitive input by normalizing the counts. Normalization involves dividing all counts by a factor that keeps the counts constant, as if all clients kept an unchanging list of rated items. In this way, as the clients slowly grow and alter their lists, the counts on the server will slowly adapt to the new state, and correlation factors will stay up to date, even as the general opinion among users changes. Such a gradual shift in opinion among television viewers occurs inevitable as television series gradually change, one program becoming more like some programs and becoming less like others. In effect, it allows the tracking of correlation over time, without tracking the actual changes to a particular client's ratings.

ADAPTIVE FILTERING ALGORITHM

As indicated previously, items may be rated by one of two algorithms, either the collaborative filtering algorithm described above, or an adaptive filtering algorithm incorporating a naïve Bayes classifier, described in greater detail herein below. It is has been empirically determined that collaborative filtering is a more reliable predictor of items that are likely to appeal to the user than the adaptive filtering algorithm. Accordingly, it is preferable that the collaborative filter rates an item. However, in the absence of collaborative filtering data, a heuristic passes invokes the adaptive filtering algorithm. Collaborative filtering data may not be present if the client has been unable to contact the server. The adaptive modeling algorithm works by using content-based filtering. In particular, it uses a program's features and the user's previously expressed preferences on individual program features to arrive at a prediction of how much the user would like the program. As previously noted, programs may be described in terms of attributes: actor, genre and director, for example. Generally, each attribute may have several values. For instance, 'genre' may have any of several hundred values; 'actor' may have any of several thousand values. Each individual value, or attribute-value pair, may be seen as a distinct program feature. Thus, genre: 'situation comedy' is a feature; actor:'Jennifer Anniston' is another feature. During the teaching phase, the user may have rated 'Jennifer Anniston' 1 thumb up and 'situation comedies' 2 thumbs up. Based on the user's expressed preferences, and program information from the TRIBUNE MEDIA SERVICES (TMS) database, which indicates that the genre feature for "Friends" is 'situation comedy' and the actor feature is 'Jennifer Anniston,' the system would assign 1 thumb up to "Friends."

In the example above, it is worth noting that, in the presence of an actor having a 1 thumb up rating and a genre having a 2 thumbs up rating, the system assigned the program 1 thumb up, rather than 2, indicating that the actor rating was weighted more heavily than the genre rating in predicting the program rating. A feature's specificity is an important determinant of the weight given to it in computing a program rating. It is apparent, that, in considering a population of features for a pool of programs, a specific actor

occurs less frequently in the population than a genre. Thus, in the example, the actor 'Jennifer Aston' would occur less frequently than genre 'situation comedy.' Thus, if a feature is rare in a population of features, and occurs in a description of a program, because of its rarity in the general population, it is probable that it is highly relevant to the program description. Accordingly, the less likely that a feature occurs in a general population of features, the more heavily weighted the feature will be in predicting a rating for the program having the feature. Thus, a specific actor may occur across several different genres, and genre will be weighted less heavily than actor for prediction of program ratings.

Significantly, the foregoing discussion has been directed to explicit feature ratings given by the user. It is preferable that new programs be rated according to explicitly stated user preferences. When the adaptive modeling algorithm initializes, the program features are evaluated. If the user has explicitly rated even one of the program features, the explicit user ratings are utilized to compute a rating for the program. In the absence, however of explicit feature ratings, the adaptive modeling algorithm employs a naïve Bayes classifier to infer feature ratings, and compute a program rating based on the inferred ratings. It is fundamental to the invention that user ratings always take precedence over inferred ratings. Thus, if the user has rated even one feature of a program, the naïve Bayes classifier is not invoked and the one rated feature is employed to compute the rating for that program. Inference happens as follows: if the user assigns an overall rating to a program, for example, "Cheers," the system evaluates the separate features of "Cheers" and assigns ratings to the feature based on the user's overall rating of the program. The inferred feature ratings are then used to compute a rating for a new, unrated program. The process of generating inferred ratings is described in greater detail below.

The system keeps a tally of how often a feature of an item occurs in a population of rated items, and the rating given to the item by the user. For example, a user may rate a program starring Jennifer Anniston two thumbs

up. Another program with another actor may be rated one thumb up. The system keeps a tally of the number of times a feature occurs in the population of rated programs, and what rating the program received, and makes an intelligent conclusion about the significance of a feature to the user, based on the feature occurrences and the ratings. Thus, if in the population of rated programs, Jennifer Anniston occurred ten times, each time in a program receiving two thumbs up, then the probability would be high that any other program she occurred in would receive two thumbs up.

A stepwise description of a naïve Bayes classifier, according to the invention follows:

As indicated above, a pool of items (programs) exists. The user of the system assigns ratings to a subset of that pool using a discrete number of levels. In the preferred embodiment, the rating is expressed as a number of thumbs up or down, corresponding to ratings of -3 to 3; to avoid ambiguity, the rating '0' is omitted from calculations. The items are described in terms of predefined attributes. For example: the main actor, the genre, the year the program was released, the duration, the language, the time it is aired, the tv channel it is broadcast on, how much of it has been viewed, and so on. Each attribute may have a plurality of values. For each value of each attribute, a vector C_x is defined (C_0 is the first attribute, C_1 the second, C_2 the third ... etc.). The length of each vector is set as the number of discrete rating levels; in the preferred embodiment, six. The vectors are used to keep track of the frequency of that feature (attribute-value pair) and the rating for each occurrence. A special global vector is kept to track the overall number of items that receive a particular rating, regardless of the features in that item. Where P is a prediction vector, $C_1 \ldots C_n$ is the feature vector for feature n, G is the global vector and there are m rating levels, P is calculated according to:

$$P(0) = \frac{C_1(0) * C_2(0) * C_3(0) \cdots C_n(0)}{G(0)} \qquad (1)$$

$$P(1)=\frac{C_1(1)*C_2(1)*C_3(1)\cdots C_n(1)}{C(1)}$$

$$P(2)=\frac{C_1(2)*C_2(2)*C_3(2)\cdots C_n(2)}{G(2)}$$

$$\bullet$$

$$\bullet$$

$$\bullet$$

$$P(m-1)=\frac{C_1(m-1)*C_2(m-1)*C_3(m-1)\cdots C_n(m-1)}{G(m-1)}$$

The rating where P shows a maximum value is the most probable rating for the feature. The distribution of the values in P is an indicator of certainty.

In classical implementations of the naïve Bayes classifier, it is assumed that for every attribute, only one value may occur at a time, like the color for a car. However for a program, multiple values may occur simultaneously. For example: for the attributes actors, directors, writers and genres, there are multiple simultaneous values, and sometimes none at all. For the purpose of predicting program ratings, the values lists for the various attributes are collapsed into aggregate genre and cast vectors for those features that occur in the program to be rated. Thus, for the purpose of predicting program ratings, two attributes are created, cast and genre.

The two attributes are different in nature, and the method of collapsing, or combining all values for an attribute is different. For the genre attribute, vectors are summed, the population of genres consisting of only a few hundred separate values. Due to the large population of actors, directors and writers, possibly numbering in the ten's of thousands, they are combined by taking the maximum frequency at each rating level. Additionally, actors are often clustered.

With the number of attributes being reduced to two, the possibility exists that either attribute can have 0 occurrences of matching preferences. Thus the input to the formula may be 0, 1 or 2 attributes. If there is only data for one attribute, the global vector is ignored, and only the product term is considered.

As mentioned above, a measure of confidence may be derived by considering the distribution of values in P. However, in the early stages of using the system, the number of items that have been rated is small, which produces extremes in the distribution of values, and would lead to unreliable confidence ratings. Instead, the confidence rating may be based on the amount of evidence for the winning rating level. If the maximum rating level is x, then all counts for every category (x) for all genres and all actors are summed. This value is called $P(x)e$, the total amount of evidence for $P(x)$. A global vector, H, is kept to track the highest count for each winning rating level that has been found during system operation. $C(x)e$ is normalized against $H(x)$ so that the confidence is only high when it is a record or near record for that bin. This system still favors 1 in the early use of the system. To give it a more sensible start, without affecting long-term behavior, a LaPlace method is used that avoids anomalies where there is very little data. Instead of confidence $= P(x)e/\ H(x)$, confidence $= (P(x)e\ +1)/(\ H(x)+2)$ is used. This makes it start at .5 initially, and the restriction on confidence relaxes as evidence grows.

To summarize the foregoing: the collaborative filtering algorithm is the preferred method of predicting program ratings. In the absence of up-to-date correlation factors provided by the server, a content-based adaptive filtering algorithm predicts program ratings. The features of a program to be rated are evaluated. If the user has explicitly rated any of the program's features, the user ratings are employed to predict a rating for the program. In predicting a rating, features of high specificity are more heavily weighted than those of low specificity. In the event that the user hasn't rated any of program's

features, a modified naïve Bayes classifier calculates the of probability of the program being assigned a particular rating, using inferred feature ratings derived from previous user ratings of programs. A probability vector allows a confidence level to be expressed for the predicted rating.

DISPLAY OF RATED ITEMS

As Figure 2 shows, rated items are displayed as a list of suggestions. Both user rated-items and items carrying predicted ratings are listed in the same display. As previously described, user ratings are differentiated from predicted ratings through the use of distinct ratings icons. The output from both prediction engines, the collaborative filtering engine and the content-based engine is scaled and integrated into the same list. As previously described, the ratings range from three thumbs up to three thumbs down, with three thumbs up being most favorable, and three thumbs down being most unfavorable, corresponding to discrete numerical ratings in a range of –3 to 3. For display, the items are sorted in descending order from most favorable to least favorable. Within each discrete rating, the items are sorted in descending order according to confidence of the prediction, the confidence level ranging from 1 to –1. Confidence level values are not necessarily discrete values, as the ratings are. It will be apparent that explicit user ratings have the highest confidence level, thus they are listed first within the ratings groups.

Although the invention has been described herein with reference to certain preferred embodiments, one skilled in the art will readily appreciate that other applications may be substituted for those set forth herein without departing from the spirit and scope of the present invention. Accordingly, the invention should only be limited by the Claims included below.

CLAIMS

What is claimed is:

1. A method of predicting items of media content most likely to appeal to a user and presenting said predictions in a graphical user interface wherein said predictions are based on preferences expressed by said user, comprising the steps of:

providing a rating system;

providing a metaphor for expressing said rating system;

providing an interactive user interface for assigning ratings by said user;

rating items according to said rating system by said user using said interactive interface;

generating ratings of new content items according to one or more predictive algorithms, based on said user ratings;

displaying said user ratings and said generated ratings in said graphical user interface.

2. The method of Claim 1, wherein items are defined by predetermined attributes, each attribute having a plurality of possible values, and wherein said step of providing an interactive user interface for assigning ratings by said user comprises the steps of:

providing interactive lists of items; and

providing interactive lists of attributes and corresponding values, wherein each unique attribute-value pair constitutes a feature.

3. The method of Claim 2, wherein said step of rating items according to said rating system by said user comprises at least one of the steps of

assigning an overall rating to an item;

assigning ratings to individual features.

4. The method of Claim 3, wherein said rating system includes values from a range of approximately –3 to 3, so that a negative number signifies an unfavorable rating, a positive number signifies a favorable rating and a '0' signifies a neutral rating.

5. The method of Claim 4, wherein said graphical metaphor utilizes "thumbs up" icons for favorable ratings and "thumbs down" icons for unfavorable ratings, and wherein the number of thumbs assigned to an item equals the numerical value of said rating.

6. The method of Claim 5, wherein said step of generating ratings comprises the steps of:

providing a collaborative filtering algorithm;

identifying new items that correlate highly with items previously rated by said user, according to said collaborative filtering algorithm; and

assigning ratings to said new items based on said correlation and said previous user rating.

7. The method of Claim 5, wherein said step of generating ratings comprises the steps of:

providing a content-based adaptive modeling algorithm;

evaluating user-assigned ratings of individual features;

assigning an overall rating to a new item defined by any of said user-rated features based on said user-assigned ratings.

8. The method of Claim 7, wherein said step of generating ratings comprises the steps of:

providing a modified naïve Bayes classifier;

pooling all features defining items assigned overall ratings by said user, except for featrues that have explicitly been rated by said user;

tallying the occurrence of each distinct feature in said pool, and weighting it according to the overall ratings of the items it defines, according to said naïve Bayes classifier; and

generating overall ratings for new items based on said tallies and weightings of said features.

9. The method of Claim 5, wherein said media content comprises any of network television programming, cable television programming, network television programming, pay-per-view television programming, movies and public-access television programming.

10. The method of Claim 9, wherein said attributes include:

genre, actor and director.

11. The method of Claim 5, wherein the “thumbs up” and “thumbs down” icons for user assigned ratings are visually distinct from those for generated ratings.

12. The method of Claim 5, wherein confidence level of said predictive algorithms increases as the number of explicit ratings increases.

13. The method of Claim 12, wherein the step of displaying said ratings comprises the steps of:

aggregating said user-rated items and outputs of said predictive algorithms into a single list;

sorting said list according to rating in descending order;

sorting items having the same rating according to confidence level in descending order; and

displaying said sorted list in said graphical user interface as a list, wherein an item is displayed accompanied by its rating icon.

14. The method of Claim 12, further comprising the step of

changing a rating by said user; and

updating the rating icon to correspond to said changed rating.

15. The method of Claim 14, wherein a user-assigned rating cannot be replaced by a generated rating.

16. A method of predicting items of media content likely to appeal to a user, based on said user's preferences, comprising at least one of the steps of:

rating a new item based on earlier user ratings of items that correlate highly with said new item according to a first predictive algorithm, said first algorithm comprising a collaborative filtering algorithm;

rating a new item according to a second predictive algorithm, said second algorithm comprising a content-based adaptive modeling algorithm, based on user ratings of specific features describing said item, wherein at least a portion of said features have previously been explicitly rated by said user; and

for a new item whose features have not been previously rated by said user, rating said new item based on previous explicit user ratings of items, according to said adaptive modeling algorithm, wherein said algorithm generates implicit ratings of features based on said explicit user ratings.

17. The method of Claim 16, wherein said collaborative filtering algorithm rates items according to correlation factors, so that an item with a high correlation factor to an item rated by said user is similarly rated.

18. The method of Claim 17, wherein said correlation factors are provided in a table of correlating items.

19. The method of Claim 18, wherein said table of correlating items comprises a plurality of pairs of items and a corresponding correlation factor for each pair.

20. The method of Claim 17, wherein said correlation factors are calculated from other users' ratings, wherein said other users' ratings are stored in one or more pair matrices, and wherein each matrix yields a correlation factor in a range of approximately –1 to 1.

21. The method of Claim 18, wherein said table of correlating items is downloaded to a client from a server.

22. The method of Claim 16, wherein said step of rating a new item according to a second algorithm comprises the steps of:

presenting said user with a list of possible features;

assigning ratings to at least a portion of the displayed features by said user;

inputting said ratings of said values to said second algorithm, wherein said algorithm rates new items, wherein features high specificity that occur infrequently are heavily weighted and considered to be reliable predictors.

23. The method of Claim 22, wherein said step of presenting said user with a list of possible features comprises:

providing an interactive user interface, wherein each attribute is displayed as a user selection on a screen, wherein selecting an attribute navigates the user to a subsequent screen displaying one or more lists of values, each unique attribute-value pair constituting a feature, wherein each list is a user selection.

24. The method of Claim 23, wherein said step of assigning ratings to at least a portion of said values by said user comprises the steps of:

selecting a list of features, wherein features constituting said list are displayed on a subsequent screen; and

assigning ratings to at least a portion of said displayed features.

25. The method of Claim 16, wherein said step of rating new items based on previous explicit user ratings of items comprises the steps of:

determining features that correlate to said user's tastes and preferences, based on previous ratings of items by said user;

optionally, presenting said user with a list of said features so that said user may interactively modify said list; and

inputting said features to said second algorithm, wherein said algorithm rates items not previously rated.

26. The method of Claim 25, wherein said second algorithm includes a modified naïve Bayes classifier, wherein said modified Bayes classifier accommodates multiple simultaneous features, and wherein said modified Bayes classifier is capable of excluding selected features.

27. The method of Claim 26, wherein user ratings comprise explicit ratings and generated ratings comprise implicit ratings, and wherein an explicit rating overrides an implicit rating.

28. The method of Claim 27, wherein explicitly rated features are excluded as inputs to said Bayes classifier so that said algorithm works only with unrated features, said unrated features comprising free-floating features.

29. The method of Claim 28, wherein said step of determining features comprises the steps of:

aggregating all free-floating features from said user-rated items into a population of features;

tallying the occurrences of unique features in said population;

assigning a weight to each unique feature, wherein a featureof high-specificity has a higher weight than one of low specificity; and

wherein an infrequently-occurring, highly-weighted feature constitutes a reliable predictor of items likely to appeal to said user.

30. The method of Claim 25, wherein said step of presenting said user with a list of said attribute-value pairs so that said user may interactively

modify said list comprises providing an interactive user interface, wherein each attribute is displayed as a user selection on a screen, wherein selecting an attribute navigates the user to a subsequent screen displaying one or more lists of values, wherein each list is a user selection.

31. The method of Claim 30, wherein said step of presenting said user with a list of said attribute-value pairs so that said user may interactively modify said list further comprises the steps of:

selecting a list of features, wherein features constituting said list are displayed on a subsequent screen;

evaluating ratings assigned to said features; and

optionally, modifying said ratings.

32. The method of Claim 16, wherein said media content comprises any of network television programming, cable television programming, network television programming, pay-per-view television programming, movies and public-access television programming.

33. The method of Claim 16, wherein said attributes include: director, actor and genre.

34. The method of Claim 16, wherein said ratings include values from a range of approximately –3 to 3, so that a negative number signifies an unfavorable rating, a positive number signifies a favorable rating and a '0' signifies a neutral rating.

35. The method of Claim 34, wherein a graphical metaphor expresses said ratings, so that a "thumbs up" icon signifies a favorable rating and a "thumbs down" icon signifies an unfavorable rating, and wherein the number of thumbs assigned is equal to the absolute value of said rating.

36. The method of Claim 35, wherein icons signifying explicit ratings are distinct from icons signifying implicit ratings.

37. The method of Claim 36, wherein confidence level of said predictive algorithms increases as the number of explicit user ratings increases.

38. The method of Claim 37, further comprising the steps of:

aggregating user-rated items and output from said predictive algorithms into a single list;

sorting said list according to rating in descending order;

sorting items having the same rating according to confidence level in descending order; and

displaying said list to said user as a list in a graphical user interface.

38. A method of predicting items of media content likely to appeal to a user, wherein a new item is rated based on ratings of features describing said item according to a content-based adaptive modeling algorithm, said method comprising one of the steps of:

predicting a rating based on features explicitly rated by said user; and

in the absence of explicitly rated features, predicting a rating based on implicitly rated features, wherein said adaptive modeling algorithm generates said implicit ratings based on previous overall ratings of items by said user.

39. The method of Claim 38, wherein said step of predicting a rating based on features explicitly rated by said user comprises the steps of:

inputting ratings of features defining said item to said algorithm;

rating said item according to said features, wherein features of high specificity are heavily weighted, and wherein an infrequently-occurring feature of high specificity constitutes a reliable predictor for said item.

40. The method of Claim 38, wherein said step of predicting a rating based on implicitly rated features comprises the steps of:

determining features that correlate to said user's tastes and preferences, based on previous ratings of items by said user;

optionally, presenting said user with a list of said features so that said user may interactively modify said list; and

inputting said features to said adaptive modeling algorithm, wherein said algorithm rates items not previously rated.

41. The method of Claim 40, wherein said adaptive modeling algorithm includes a modified naïve Bayes classifier, wherein said modified Bayes classifier accommodates multiple simultaneous features, and wherein said modified Bayes calssifier is capable of excluding selected features.

42. The method of Claim 39, wherein an explicit rating overrides an implicit rating.

43. The method of Claim 42, wherein explicitly rated features are excluded as inputs to said Bayes classifier so that said algorithm works only with unrated features, said unrated features constituting free-floating features.

44. The method of Claim 43, wherein said step of determining features comprises the steps of:

aggregating all free-floating features from said user-rated items into a population of features;

tallying the occurrences of unique features in said population;

assigning a weight to each unique feature, wherein a feature of high-specificity has a higher weight than one of low specificity; and

wherein an infrequently-occurring, highly-weighted feature constitutes a reliable predictor of items likely to appeal to said user.

45. The method of Claim 38, wherein said step of presenting said user with a list of said attribute-value pairs so that said user may interactively modify said list comprises providing an interactive user interface, wherein each attribute is displayed as a user selection on a screen, wherein

selecting an attribute navigates the user to a subsequent screen displaying one or more lists of values, wherein each list is a user selection.

46. The method of Claim 45, wherein said step of presenting said user with a list of said features so that said user may interactively modify said list further comprises the steps of:

selecting a list of features, wherein features constituting said list are displayed on a subsequent screen;

evaluating ratings assigned to said features; and

optionally, modifying said ratings.

47. The method of Claim 38, wherein said media content comprises any of network television programming, cable television programming, network television programming, pay-per-view television programming, movies and public-access television programming.

48. The method of Claim 38, wherein said ratings include values from a range of approximately –3 to 3, so that a negative number signifies an unfavorable rating, a positive number signifies a favorable rating and a '0' signifies a neutral rating.

49. The method of Claim 48, wherein confidence level of said adaptive modeling algorithm increases with increasing numbers of explicitly rated items.

50. The method of Claim 49, wherein a graphical metaphor expresses said ratings, so that a "thumbs up" icon signifies a favorable rating and a "thumbs down" icon signifies an unfavorable rating, and wherein the number of thumbs assigned is equal to the absolute value of said rating.

51. The method of Claim 50, wherein icons signifying explicit ratings are distinct from icons signifying implicit ratings.

52. The method of Claim 50, further comprising the steps of:

aggregating user-rated items and output of said algorithm into a single list;

sorting said list according to rating in descending order;

sorting items having the same rating according to confidence level in descending order; and

displaying said list to said in a graphical user interface.

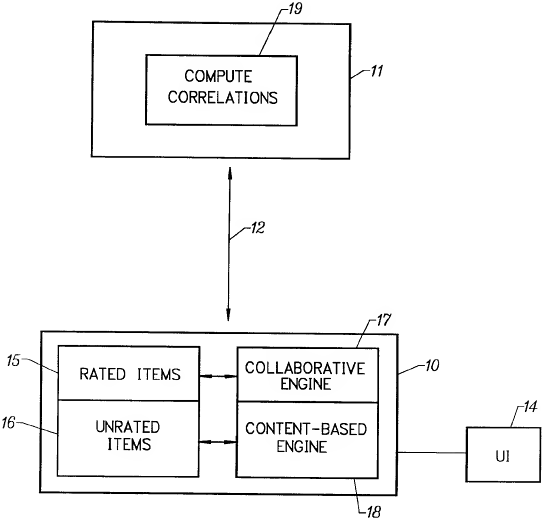
19
COMPUTE CORRELATIONS
11
12
17
15
RATED ITEMS
COLLABORATIVE ENGINE
10
14
16
UNRATED ITEMS
CONTENT-BASED ENGINE
UI
18

FIG. 1

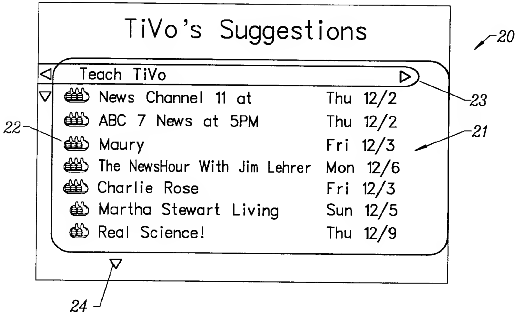
TiVo's Suggestions
Teach TiVo
News Channel 11 at Thu 12/2
ABC 7 News at 5PM Thu 12/2
Maury Fri 12/3
The NewsHour With Jim Lehrer Mon 12/6
Charlie Rose Fri 12/3
Martha Stewart Living Sun 12/5
Real Science! Thu 12/9
20
21
22
23
24

FIG. 2

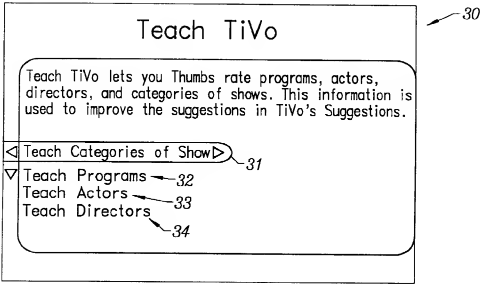
Teach TiVo
Teach TiVo lets you Thumbs rate programs, actors, directors, and categories of shows. This information is used to improve the suggestions in TiVo's Suggestions.
Teach Categories of Show
Teach Programs
Teach Actors
Teach Directors
30
31
32
33
34

FIG. 3

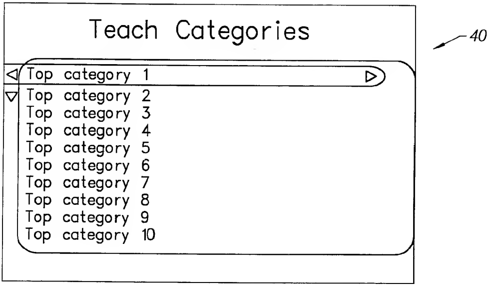
Teach Categories
Top category 1
Top category 2
Top category 3
Top category 4
Top category 5
Top category 6
Top category 7
Top category 8
Top category 9
Top category 10
40

FIG. 4

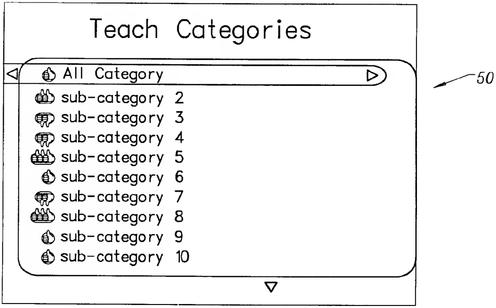
Teach Categories
All Category
sub-category 2
sub-category 3
sub-category 4
sub-category 5
sub-category 6
sub-category 7
sub-category 8
sub-category 9
sub-category 10
50

FIG. 5

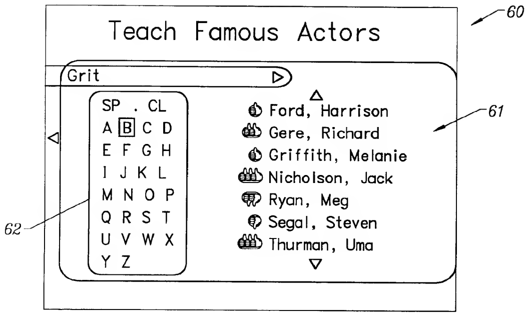
60
Teach Famous Actors
Grit
SP . CL
A B C D
E F G H
I J K L
M N O P
Q R S T
U V W X
Y Z
Ford, Harrison
Gere, Richard
Griffith, Melanie
Nicholson, Jack
Ryan, Meg
Segal, Steven
Thurman, Uma
61
62

FIG. 6

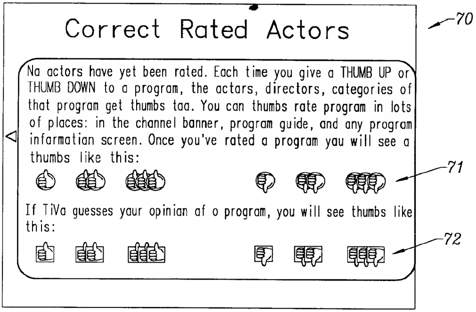
70
Correct Rated Actors
No actors have yet been rated. Each time you give a THUMB UP or THUMB DOWN to a program, the actors, directors, categories of that program get thumbs too. You can thumbs rate program in lots of places: in the channel banner, program guide, and any program information screen. Once you've rated a program you will see a thumbs like this:
71
If TiVo guesses your opinion of o program, you will see thumbs like this:
72

FIG. 7

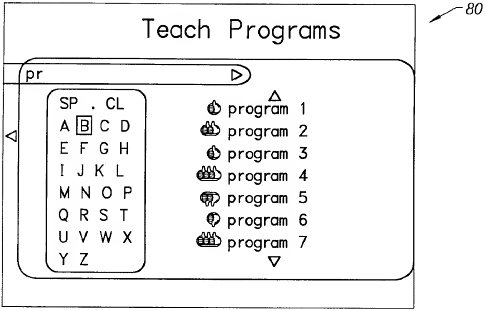
80
Teach Programs
pr
SP . CL
A B C D
E F G H
I J K L
M N O P
Q R S T
U V W X
Y Z
program 1
program 2
program 3
program 4
program 5
program 6
program 7

FIG. 8

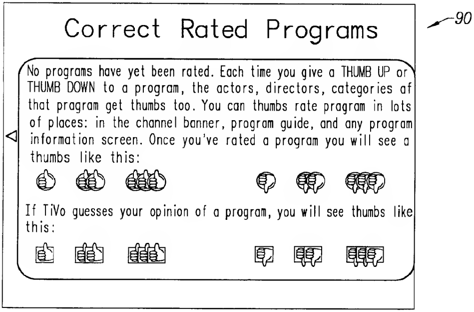
90
Correct Rated Programs
No programs have yet been rated. Each time you give a THUMB UP or THUMB DOWN to a program, the actors, directors, categories of that program get thumbs too. You can thumbs rate program in lots of places: in the channel banner, program guide, and any program information screen. Once you've rated a program you will see a thumbs like this:
If TiVo guesses your opinion of a program, you will see thumbs like this:

FIG. 9

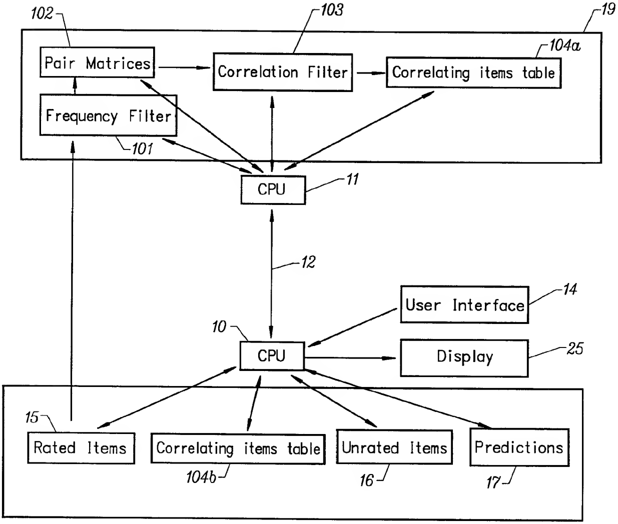
102
103
19
Pair Matrices
Correlation Filter
104a
Correlating items table
Frequency Filter
101
CPU
11
12
14
User Interface
10
CPU
Display
25
15
Rated Items
Correlating items table
Unrated Items
Predictions
104b
16
17

FIG. 10

INTERNATIONAL SEARCH REPORT

International Application No
PCT/US 00/33876

A. CLASSIFICATION OF SUBJECT MATTER
IPC 7 H04N5/445 H04N7/173

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
IPC 7 H04N

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

EPO-Internal, WPI Data, PAJ, INSPEC

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category °	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No
A	B. SMITH, P. COTTER: "Surfing the Digital Wave, Generating Personalised TV Listings using Collaborative, Case-Based Recommendation" PROCEEDINGS OF THE 3RD INTERNATIONAL CONFERENCE ON CASE-BASED REASONING, ICCBR-99, 27 - 30 July 1999, pages 562-571, XP000997650 Seeon, Germany page 565, paragraph 2; figure 2 page 566, paragraph 1 page 568, paragraph 4 ---	1-7,9, 11,16, 17, 22-25, 30-32, 34-36, 38-40, 45-48, 50-52

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[X] Further documents are listed in the continuation of box C.

[X] Patent family members are listed in annex.

° Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier document but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
4 April 2001	12/04/2001

Name and mailing address of the ISA	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL – 2280 HV Rijswijk Tel. (+31-70) 340-2040, Tx. 31 651 epo nl, Fax: (+31-70) 340-3016	Sindic, G

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Internatic Application No
PCT/US 00/33876

C.(Continuation) DOCUMENTS CONSIDERED TO BE RELEVANT

Category °	Citation of document, with indication,where appropriate, of the relevant passages	Relevant to claim No.
A	WO 99 35830 A (STRONG ROBERT JOHN ;THOMSON CONSUMER ELECTRONICS (US); WESTLAKE MA) 15 July 1999 (1999-07-15) page 5, line 10 - line 25 page 6, line 12 - line 17 page 7, line 3 - line 21	1-4,16, 22-24, 32-34, 38,47,48
A	US 5 758 257 A (HERZ FREDERICK ET AL) 26 May 1998 (1998-05-26) column 5, line 33 - line 52 column 11, line 7 - line 25 column 12, line 11 - line 28 column 14, line 11 - line 34 column 15, line 34 - line 43 column 24, line 66 -column 25, line 6 column 31, line 6 - line 13 column 34, line 13 - line 23	1-10, 16-34, 38-48

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INTERNATIONAL SEARCH REPORT

Information on patent family members

International Application No
PCT/US 00/33876

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
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US 5758257 A	26-05-1998	AU 703247 B	25-03-1999
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